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# **Impact of Information Sharing and Order Aggregation Strategies on Supply Chain Performance**

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# **Impact of Information Sharing and Order Aggregation Strategies on Supply Chain Performance**

## **Abstract**

With the extensive discussion of Supply Chain Management concepts in the recent past, issues concerning efficient inventory policies gain in importance. Several analytical models as well as simulation studies revealed inventory reductions for the entire supply chain by applying information sharing strategies. However, discrepancies in the published results concerning the effects on individual supply chain members exist. By using discrete event simulation we analyze various approaches of differently aggregated order data compared to shared demand data. Our experiments show that, even for a constant demand pattern, suppliers cannot accurately estimate demand means and variances due to time-depending order quantities and biasing effects of order inter-arrival times. Whereas information sharing can reduce safety stocks and inventories, it may lead to considerably lower service levels.

## **1 Introduction**

In the recent Supply Chain Management (SCM) discussion, control and management of inventories have attracted increasing attention. Research on the bullwhip effect revealed substantial inefficiencies in the supply chain, resulting, amongst others, from information inaccuracy [1,2]. To overcome such inefficiencies, sharing information (e.g., point of sales data) along the entire supply chain has been proposed. Recent research revealed inventory reductions for the entire supply chain adopting information sharing strategies. However, the published results differ significantly in the intensity of the effects for individual supply chain members. These discrepancies may be, among others, the result of simplifications in the model structure as such simplifications have a large impact on the calculation of reorder points and safety stocks.

Using discrete event simulation we analyze the effect of information sharing on inventory and service levels for each of the supply chain members. In contrast to prior research we use different aggregation levels of either traditional order data or shared demand data as it might influence the

efficiency of basic reordering policies. To account for different supply chain settings, four demand patterns were considered (constant, season, trend, season & trend).

The remainder of the paper is organized as follows. Section 2 discusses the existing literature on information sharing strategies focusing on simulation studies. Section 3 describes the simulation model under investigation. In Section 4 the simulation results are discussed, whereas in Section 5 the main results are summarised and directions for future research are suggested.

## **2 Literature Review**

The rapid advancement of information technology has led to several opportunities for a fast exchange of information. To analyze the effects of shared information on supply chain performance several analytical models have been developed [e.g., 3,4,5,6,7,8,9,10]. As supply chains often are too complex to be analyzed analytically, several researchers tried to identify the impact of shared information by using simulation techniques.

Closs et al. investigate the effects of information sharing on inventory and service levels in a four-stage supply chain [11]. The authors show inventory reductions for the entire supply chain and also increasing service-levels.

Based on real-life data obtained from Hewlett Packard, Waller et al. developed a simulation model in which they examine the effects of shared information on inventory levels under fixed service levels [12]. They conclude that available daily demand information for suppliers may lead to decreasing inventory levels for the entire supply chain.

On the basis of real data from the agricultural sector, Southard tries to determine the cost savings resulting from information sharing in a Vendor Managed Inventory (VMI) partnership of a two-stage supply chain [13]. Southard concludes that the costs for both entities in the supply chain can be reduced without a service level decrease by sharing inventory data and shifted inventory responsibility.

Zhao et al. analyze the effects of demand structure, accuracy of forecasts and information sharing on supply chain costs in a two-stage supply chain [14]. The declared results show significantly different impacts of information sharing on the performance of the manufacturer and the retailer. As supplier costs can be reduced using information sharing, the costs for the retailer rise remarkably in several settings.

Based on actual demand data, Smaros et al. investigate the impact of information sharing in a VMI partnership when demand data is only partially available [15]. The key finding is that, even partially available demand data can improve production and inventory control efficiency.

Nevertheless the value of information sharing greatly depends on the replenishment frequencies and the production planning cycle.

Yang et al. investigate, among others, the effects of demand fluctuation, delivery frequency, number of retailers, and availability of demand information [16]. The authors show a strong impact of demand variability on inventory levels. Interestingly, information sharing of demand shows no significant impact neither for the manufacturer nor the retailer.

Angulo et al. analyze the impact of data quality of shared information on inventory and service levels [17]. They find positive effects of information sharing for the outlets resulting from a higher replenishment frequency. However, imprecise information may lead to increased inventory levels for the manufacturer. Furthermore, imprecise information and delays have to be eliminated as they lead to increased inventory levels for all supply chain members.

Chatfield et al. enhance the classical setting of the Beer Distribution Game with information sharing opportunities and analyze the effects of availability and quality of information on the bullwhip effect [18]. They show reductions of the bullwhip effect by sharing information. Thus, information sharing is beneficial particularly for upstream supply chain members.

Lau et al. analyze the impact of information sharing on inventory levels, service levels, and supply chain costs in a highly complex simulation model [19]. They conclude that information sharing leads to cost reductions for all supply chain members. However, decreasing inventory levels lead to massively higher backorders.

Yan and Woo analyze the impact of shared demand or shipment data on inventory levels and backorders in a two-stage supply chain for demand structures changing over time [20]. They show that information sharing leads to inventory reductions for the supplier but can result in increased backorders.

The study of Sahin and Robinson is one of the few publications that also take production planning aspects into consideration [21]. The authors investigate the effects of shared information and advanced coordination of material flows in a make-to-order environment. They show positive effects of information sharing for the supplier. However, larger benefits can be achieved through better coordination of material flows.

The review of the literature revealed contradictory effects of information sharing on supply chain performance. Although most of the studies revealed to some extent substantial inventory reductions by applying information sharing strategies, the effects on the service levels are quite different. One of the reasons for the discrepancies in the results may arise due to simplifications in the structure of the models. Particularly in linear supply chains, the demand for suppliers is not continuous since the customer batches its demand into orders. In such a setting it seems quite obvious, that sharing

information may bring benefits as it allows suppliers a more accurate representation of the end consumer demand which leads to more appropriate calculations of reorder points and safety stocks. However, this leads to the question if merely an aggregation of incoming orders into larger time units may result in better reorder point and safety stock calculations through lower order variability. Hence, the need for safety stocks to protect against uncertainty may be reduced for suppliers.

This study explores how differently aggregated order data affect inventory and service levels in a linear three-stage supply chain and compares the results against various levels of information sharing. By performing additional sensitivity analysis, we try to identify critical parameters and give conjectures for the different results in prior literature.

### 3 Model Specification

A discrete event simulation model was developed by using the EXTEND simulation software ([www.imaginethatinc.com](http://www.imaginethatinc.com)). The experiments assume a three-stage supply chain with one manufacturer, one distributor, and one retailer serving several customers. The model and the parameter settings are described in the following sections.

#### 3.1. Inventory Control

Each echelon decides on when to order based on a continuous inventory review policy, which determines a reorder point for stochastic demand. When inventory position falls below the reorder point, an order is placed to raise inventory to a target level. The reorder point may be calculated as [22]

$$ROP = L \cdot E(x) + \sqrt{L} \cdot z \cdot \sigma_x,$$

where  $L \cdot E(x)$  is the mean demand during lead time and  $\sqrt{L} \cdot z \cdot \sigma_x$  represents the safety stock which depends on the standard deviation of demand, the lead time, and a constant service factor often associated with a target service level based on the assumption of normally distributed demand. For each echelon a safety factor of  $z = 1.88$  was chosen, which corresponds to a service level of 97%. Lead time parameters are set as follows: For the manufacturer 14 days, the distributor 7 days, and the retailer 3 days.

For each supply chain member a fixed order quantity is assumed. To avoid extremely high order frequencies, the order quantities are set higher than the expected reorder points. The order quantities are chosen to be 10000 for the manufacturer, 2000 for the distributor, and 400 for the retailer. However, even though the inventory review is continuous, it is possible that the inventory position is lower than the reorder point due to batched orders. To take this into consideration, the

order quantity has to compensate for the difference of the inventory and the reorder point. Thus the effective order quantities may be higher than the fixed values and may vary over time.

If on-hand inventory is sufficient, the quantity ordered by the customer is completely delivered. In out of stock situations suppliers deliver the available quantity and note backorders for the unfilled demand, which are delivered as soon as inventory becomes available. To ensure that sufficient inventory is available at the beginning of the simulation, initial inventories are set at 5000 for the manufacturer, at 1000 for the distributor, and at 200 units for the retailer. Table 1 gives an overview of the relevant parameters for inventory management.

	<b>Manufacturer</b>	<b>Distributor</b>	<b>Retailer</b>
Initial Inventory	5000	1000	200
Order Quantity	10000	2000	400
Lead Time	14	7	3
Target Service Level	97%	97%	97%

Table 1: Parameter settings for inventory management in the modelled supply chain

### 3.2. Information Aggregation

A major task in determining adequate reorder points is the estimation of mean demand and its variance during lead time. In cases of continuous demand, forecasting demand is straightforward. As demand for suppliers becomes discrete, forecasting can be a challenging task. Even if the incoming orders are relatively constant, the order inter-arrival time may vary, depending on the real end consumer demand. Hence, suppliers facing discrete demand can not accurately estimate mean and variance of the demand during lead time. To reduce this problem, aggregating demand data into larger time units might be beneficial. However, providing demand data for suppliers seems to be a more efficient solution as it reduces the problem of discrete demand.

The focus of this paper lies in the analysis of differently aggregated order data or shared demand information. Simple mean and variance estimations are examined as well as moving average and moving variance based on differently available demand data. Table 2 shows the seven scenarios investigated. Scenarios 1 to 4 are based on order data, whereas scenarios 5 to 7 are based on shared demand data.

Scenario	Estimation of demand mean and variance based on orders
Scenario 1	Simple mean and variance based on weekly orders
Scenario 2	Simple mean and variance based on monthly orders
Scenario 3	Moving average/variance of weekly orders (12 weeks)
Scenario 4	Moving average/variance of monthly orders (3 months)
Scenario	Estimation of demand mean and variance based on shared information
Scenario 5	Moving average/variance of daily demand data provided by customer (30 days)
Scenario 6	Moving average/variance of weekly demand data provided by customer (12 weeks)
Scenario 7	Moving average/variance of monthly demand data provided by customer (3 months)

Table 2: Description of aggregation scenarios

### 3.3. Demand Generation

To consider different demand characteristics and to investigate their impact on the seven information aggregation scenarios, four customer demand patterns were taken into account (stationary, season, trend, season & trend). The patterns were generated based on the following formula [14]:

$$Demand_t = initial\ mean + daily\ std \cdot snormal() + trend \cdot t + season \cdot \sin\left(\frac{2\pi}{360} \cdot t\right).$$

$Demand_t$  represents the daily demand for day  $t = (1, 2, 3, \dots, N)$  consisting of initial mean, standard deviation of daily demand and values for trend or seasonal demand pattern generation. For the simplest demand pattern without seasonality or trend, the mean daily demand is 100 with a standard deviation of 20. To ensure that mean demand is approximately 100 also for trendy demand, initial mean is set to 40. Parameter settings of all demand patterns are shown in Table 3.

Pattern	Initial Mean	Daily STD	Trend	Season
Pattern 1	100	20	0	0
Pattern 2	100	20	0	20
Pattern 3	40	20	0.1	0
Pattern 4	40	20	0.1	20

Table 3: Parameters for demand generation

As the demand generator includes a normally distributed random number, the patterns vary for each simulation run. A graphical illustration of possibly generated patterns is shown in Figure 1.

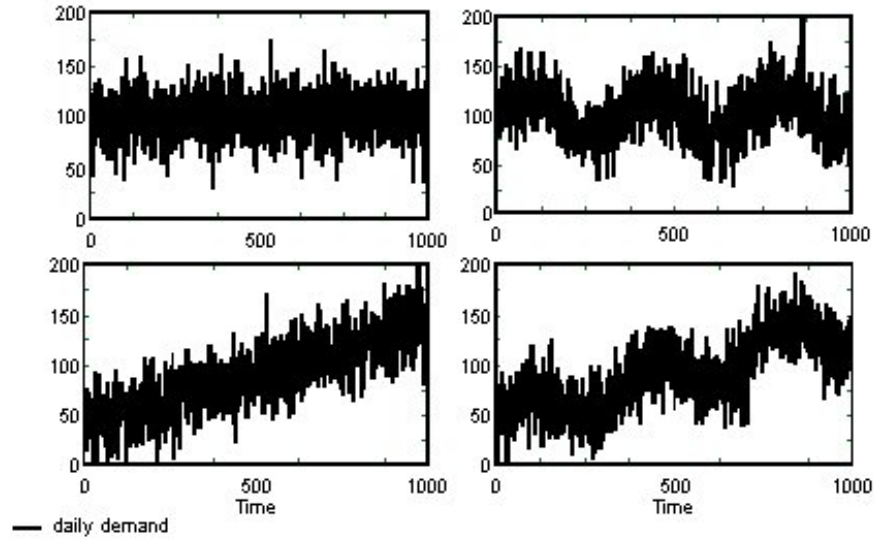


Figure 1: Visualization of investigated demand patterns

### 3.4. Performance Measures

To evaluate the seven aggregation scenarios in combination with the four demand patterns, the following performance measures were used:

- Mean inventory level
- Mean safety stock
- Proportion of complete numbers of deliveries (service level alpha)
- Ratio of delivery quantity and order quantity (service level beta)

The distinction between two service levels is appropriate to examine on one hand, how often a delivery is not complete, and, on the other hand, to quantify the percentage of products not delivered in time. For instance, if a supplier ships in half of the cases only 95% of ordered products, the service level alpha would be only 50%, whereas the service level beta equals 97.5%.



## 4 Results and Discussions

For each of the four demand patterns and the seven scenarios discussed in the previous sections, 10 simulation runs were performed. As information sharing is investigated for the manufacturer as well as for the distributor, a total of  $4 \times 7 \times 10 \times 2 = 560$  runs was executed and compared, where one run consists of 1000 days. For the statistical analysis the first 200 days of each simulation run were deleted to compensate warm-up effects. Detailed results are presented in the following sections.

### 4.1. Results for the Distributor

Simulation results for the distributor are shown in Table 4. The effect of the seven data aggregation scenarios on inventories, safety stocks and service levels are compared for four different demand patterns. The table clearly shows the inefficiency of inventory control based on order data. On one hand it leads to higher mean inventories resulting from exaggerated safety stocks, on the other hand it overshoots the desired service level of 97% by far. The aggregation of order data into larger time units combined with forecasts (scenario 4) leads to significantly lower safety stocks for all demand patterns. A maximum reduction of 58% can be achieved for trend demand. As the aggregation scenarios 3 and 4 include forecasted demand data, they generally result in a reduction of safety stocks especially when demand is not constant. Thus, forecast implementation is highly appreciated for more efficient inventory control for non-stationary demand.

The aggregation of shared demand data has contradictory effects on safety stocks and service levels. Sharing actual (daily) demand data leads to reduced safety stocks in almost all demand settings, but may result in considerably lower service levels. Thus, information sharing alone does not overcome the traditional trade-off between high inventory and low service levels, and vice versa. However, depending on the target service level, information sharing may result in substantial benefits. For seasonal demand, the maximum safety stock reduction compared with the best solution of order data aggregation is approximately 64%. Interestingly, the beta service levels are about 99% or above for all scenarios. This leads to the conclusion that information sharing results in a higher proportion of incomplete deliveries but the majority of shipped products arrive in time.

	Order Data				Shared Demand Data		
	1	2	3	4	5	6	7
	<b>constant</b>						
Mean Inventory	1549	1365	1547	1327	1217	1221	1202
Mean Safety Stock	430	250	440	214	99	103	81
Service Level (alpha)	100.0%	100.0%	100.0%	99.2%	97.0%	96.8%	95.0%
Service Level (beta)	100.0%	100.0%	100.0%	99.9%	99.7%	99.7%	99.3%
	<b>season</b>						
Mean Inventory	1581	1623	1537	1394	1235	1261	1331
Mean Safety Stock	442	480	414	276	99	125	203
Service Level (alpha)	100.0%	99.9%	100.0%	98.5%	96.0%	96.1%	98.1%
Service Level (beta)	100.0%	100.0%	100.0%	99.7%	99.4%	99.3%	99.6%
	<b>trend</b>						
Mean Inventory	1351	1437	1477	1330	1233	1213	1239
Mean Safety Stock	416	511	359	214	98	103	118
Service Level (alpha)	98.5%	99.2%	98.7%	97.0%	95.1%	93.1%	95.1%
Service Level (beta)	99.7%	99.9%	99.7%	99.2%	99.0%	98.3%	98.9%
	<b>season&amp;trend</b>						
Mean Inventory	1395	1516	1475	1402	1259	1266	1325
Mean Safety Stock	448	558	366	275	99	124	203
Service Level (alpha)	98.3%	98.9%	99.0%	97.6%	95.3%	95.2%	96.4%
Service Level (beta)	99.5%	99.9%	99.8%	99.5%	98.8%	98.7%	99.2%

Table 4: Results for distributor for different demand patterns

To ensure that the results are not biased by the parameter settings, the simulation was executed with different order quantities for customers. The order quantities of the retailer were raised from initial 400 to 600 or 800 units. Figure 2 shows the safety stocks and the alpha service levels for the distributor for constant demand.

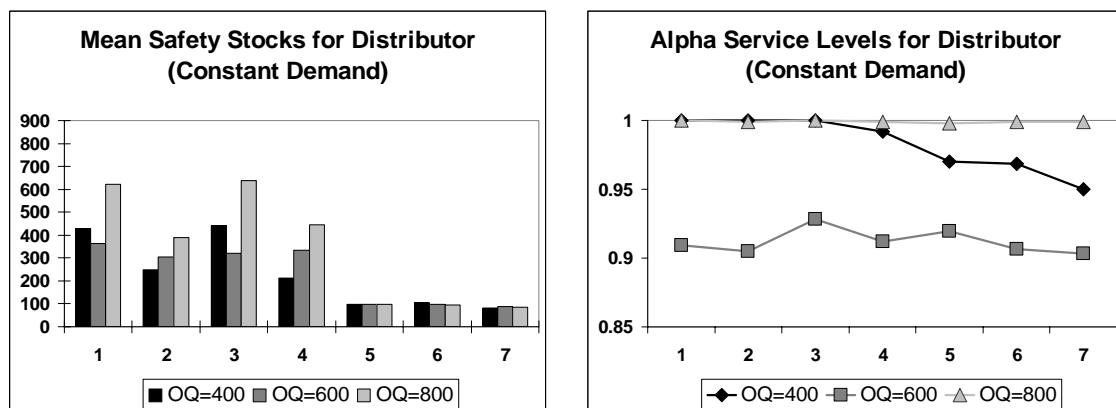


Figure 2: Sensitivity analysis for the distributor (constant demand)

It can be seen that safety stocks are massively lower in cases of shared demand data (scenario 5 to 7) for all order quantities. This effect arises due to the inefficient reorder point calculations based

on order data. The inefficiency comes, among others, from resulting order inter-arrival times associated with the order quantities. For instance, an order quantity of 400 units leads to a mean order inter-arrival time of 4.5 days, resulting in variable numbers of incoming orders from one week to another. An aggregation into monthly order data can mitigate some of the biases, but can not completely reduce the inefficiencies.

However, the safety stock reductions achieved by information sharing may result in considerably lower service levels. Interestingly, an order quantity of 800 units results in a service level of about 100%. The reason for this effect lies again in the resulting inter-arrival time of incoming orders. As the inter-arrival time is 8.5 and thus slightly higher than the lead time of 7 days for the distributor, the manufacturer's delivery arrives before the next retailer order comes in, resulting in a higher service level.

Figure 3 shows the results for the demand pattern containing trend and seasonal effects (pattern 4). Due to unstable demand, a higher amount of safety stock is necessary to protect against uncertainty. To react faster on demand changes, an aggregation of shared demand data into larger time units is not appropriate and results in higher safety stocks (scenario 7) for all order quantities considered. Similar safety stock reductions as for constant demand can be observed, whereas higher order quantities lead to lower service levels for all aggregation scenarios.

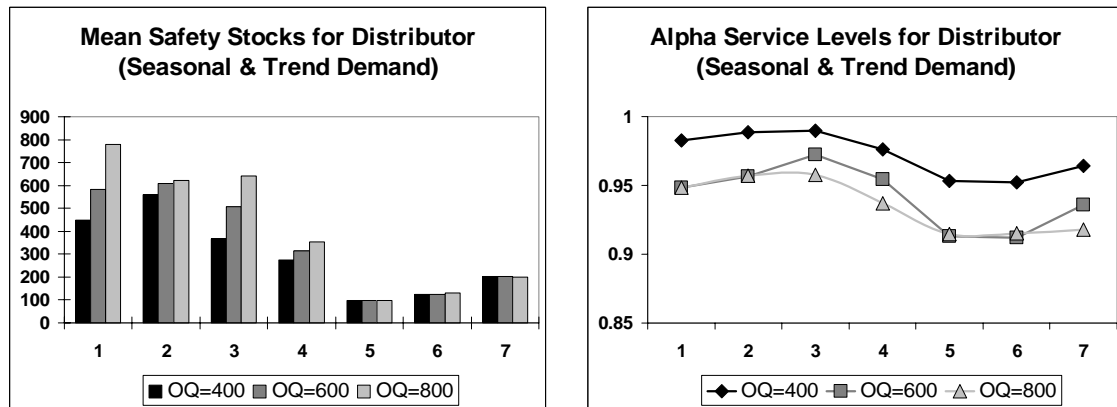


Figure 3: Sensitivity analysis for the distributor (season & trend)

## 4.2. Results for the Manufacturer

As can be seen in Table 5, inefficiencies of applying traditional stochastic inventory policies based on order data can be observed also for the manufacturer. The benefits obtained from information sharing are even more striking for the manufacturer than for the distributor in terms of lower mean inventories and safety stocks for constant demand.

	<b>Order Data</b>				<b>Shared Demand Data</b>		
	<b>1</b>	<b>2</b>	<b>3</b>	<b>4</b>	<b>5</b>	<b>6</b>	<b>7</b>
	<b>constant</b>						
Mean Inventory	8505	7238	8575	7319	5906	5898	5894
Mean Safety Stock	2756	1432	2878	1578	138	139	127
Service Level (alpha)	100.0%	100.0%	100.0%	98.6%	98.6%	98.4%	97.8%
Service Level (beta)	100.0%	100.0%	100.0%	99.6%	100.0%	99.9%	99.9%
	<b>season</b>						
Mean Inventory	8600	7352	8569	7321	5952	5954	6086
Mean Safety Stock	2768	1497	2847	1390	140	179	291
Service Level (alpha)	100.0%	100.0%	100.0%	97.2%	96.2%	96.3%	98.1%
Service Level (beta)	100.0%	100.0%	100.0%	99.4%	99.5%	99.7%	99.8%
	<b>trend</b>						
Mean Inventory	7799	6655	8463	7035	5870	5843	5744
Mean Safety Stock	2453	1324	2805	1181	137	143	169
Service Level (alpha)	100.0%	99.4%	100.0%	97.3%	94.0%	94.1%	93.0%
Service Level (beta)	100.0%	100.0%	100.0%	99.4%	99.2%	99.4%	98.8%
	<b>season&amp;trend</b>						
Mean Inventory	7815	6610	8679	7100	5867	5948	5992
Mean Safety Stock	2473	1356	2773	1337	140	174	286
Service Level (alpha)	100.0%	97.8%	100.0%	97.8%	94.2%	96.0%	95.7%
Service Level (beta)	100.0%	99.3%	100.0%	99.6%	98.9%	99.5%	99.5%

Table 5: Results for manufacturer for different demand patterns

The aggregation of order data into larger time units leads to significantly lower safety stocks for all demand patterns. A maximum reduction of approximately 58% can be achieved also for the manufacturer if demand contains trends.

The aggregation of shared demand data has contradictory effects on safety stocks and service levels. Sharing actual (daily) demand data leads to reduced safety stocks in almost all demand settings, but may result in decreases of alpha service levels. Nevertheless, beta service levels are above 99% in almost every setting. For constant demand, the safety stock reduction compared with the best solution of order data aggregation is approximately 89% if information is shared.

A similar sensitivity analysis with varying order quantities was also performed for the manufacturer. The order quantities for the Distributor were decreased from 2000 to 1500 or 1000 units. Figure 4 shows the safety stocks and the alpha service levels for the manufacturer for the constant demand pattern (pattern 1).

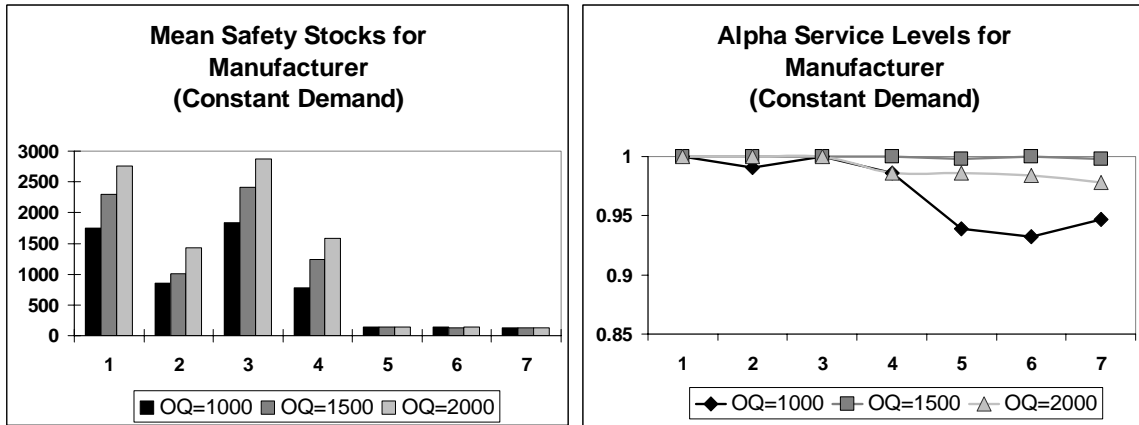


Figure 4: Sensitivity analysis for the manufacturer (constant demand)

Obviously, the safety stocks are higher with larger order quantities coming from downstream distributor in case of reorder point calculations based on order data (scenario 1 to 4). As order inter-arrival times are too large for an efficient forecast based on weekly demand, aggregated data is beneficial for all order quantities considered. Again, massive safety stock reductions are achieved through shared demand data (scenario 5 to 7) for all order quantities considered.

However, the safety stock reductions achieved by information sharing may result in lower service levels in several cases. The high service level of 100% achieved by an order quantity of 1500 can be explained due to the fact that the inter-arrival time is slightly higher than the lead time of the manufacturer. Thus, the deliveries arrive before the next order of downstream customers is placed.

Figure 5 shows the results for the demand pattern containing trend & seasonal effects (pattern 4). Similar safety stock reductions to constant demand can be achieved by information sharing. As the inter-arrival time of incoming orders has higher variability, no biasing effects concerning service levels can be observed. However, the striking benefits of information sharing are not due to current demand data, but are the results of inefficient reorder point and safety stock calculations using order data in a linear supply chain setting.

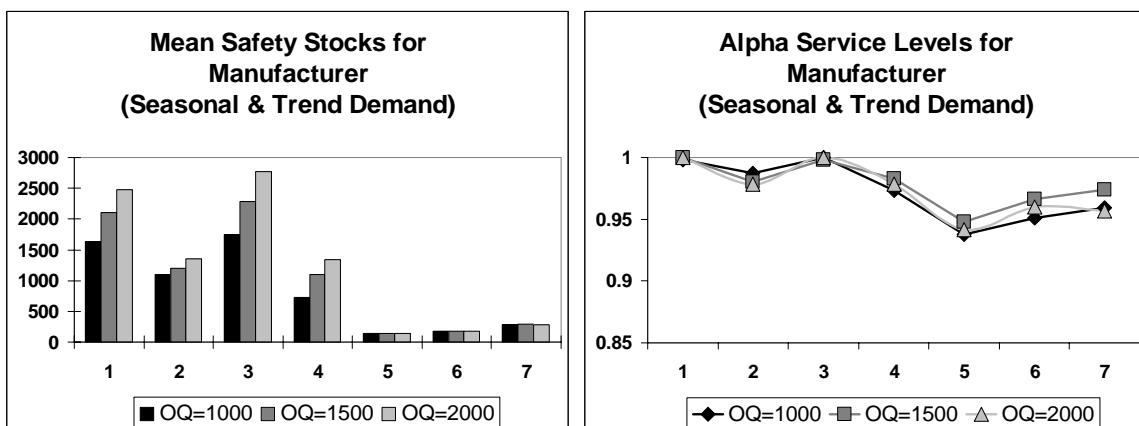


Figure 5: Sensitivity analysis for the manufacturer (season & trend)

## 5 Conclusions

This simulation study supports previous research results that information sharing is well suited to reduce safety stocks and inventory levels. However, it also shows that service levels are negatively affected by the inventory reduction. As higher demand uncertainty leads to larger variability of inter-arrival times for suppliers, sharing actual information is superior to sharing aggregated information. Furthermore, sensitivity analyses revealed a substantial impact of order quantities on supply chain performance.

In contrast to previously published results the main reason for the significant inventory reduction may not be the implementation of an information sharing procedure but inappropriate computations of the safety stock in cases without information sharing. Even if customer demand is normally distributed, the incoming orders at the upstream companies will by no means be normally distributed in a linear supply chain, since the order quantities influence the standard deviation of demand at the upstream companies heavily. Often the standard deviation of demand will be overestimated, resulting in unnecessarily high safety stocks. Thus, results of simulation studies of linear supply chains may be strongly biased by inappropriate computations of safety stocks and reorder points. For a fair comparison, the safety factors  $z$  should be adjusted in such a way that identical target service levels result without and with information sharing.

Future research has to be aware of the far-reaching effects resulting from rather unspectacular parameter settings like order quantities. Furthermore, the impact of lead time variability has to be analyzed as one may assume biasing effects of fixed lead times on the efficiency of reorder point calculations. The extension of linear supply chain simulation models to supply networks with many customers may lead to normally distributed demand for suppliers. Therefore the analysis of linear supply chains may be an inappropriate simplification for studying real supply networks.

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